Fragmentation and stability of markets

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Abstract

Trading skills are highly rewarded in practice but largely ignored in theoretical models of financial markets. This paper demonstrates the importance of skills by exploring their interaction with market fragmentation and market stability. We consider a computational model where traders' abilities to accurately price assets are endogenous. In contrast to models that do not consider skills, we find that centralising markets can lead to poorer price discovery and less resilience to shocks because it increases the equilibrium proportion of unskilled traders.

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1 Introduction

Trading skills command huge premia in the job market for professionals, particularly in the financial sector. Despite this, skills are mostly ignored in the academic literature on asset markets. Bayesian rationality, the mainstay of decision theory, simply disregards the possibility that some investors may not have the ability to make good decisions: In the standard model all economic agents are able to write down the correct equilibrium relations and solve the resulting optimisation problem. In that world, information matters, but skills do not. Empirical evidence, however, shows that markets are populated by both skilled and unskilled traders, see, e.g., Oliven and Rietz (2004); Barras et al. (2010); Fama and French (2010); Barber et al. (forthcoming).

This paper presents a computational equilibrium model of a market for financial assets in which skills are endogenously determined. We define skill as a trader's ability to price previously unseen financial contracts correctly. A skilled trader, therefore, follows an asset pricing theory that enables her to make good decisions on the purchase or sale of incorrectly valued assets. Although skill is irrelevant in perfectly efficient markets, it matters when a trader has to post a price at which others can trade, e.g., in order-driven markets, or when asset prices in a competitive market deviate from their fair values.

Traders develop pricing skills through learning. We apply an evolutionary learning process where natural selection ensures that only profitable trading strategies survive. The approach is motivated by human decision-making behaviour in 'large worlds', i.e., situations in which it is impossible to foresee all potential consequences of one's actions. Binmore (2007) argues that in large worlds Bayesian decision theory has to be replaced by other forms of learning and decision-making. Some progress towards that end has been made in game theory, notably by Ellison and Fudenberg (1993), where the players apply decision rules learned in one set of games when playing a new game in which they have no prior experience. This learning mechanism is a key feature in the model considered here. It describes an adaptive market in the sense of Lo (2004): The agents must either learn and become skilled or free-ride on others' skills, and their tendency to do the one or the other depends upon the institutional setting and the behaviour of other traders.

The model is used to explore the equilibrium relationship between skills, market fragmentation and market stability. We consider a market structure with multiple trading venues. The market is centralised if there are few venues and many traders at each venue, and fragmented if there are many venues and few traders at each venue. We find that a move from a fragmented to a centralised market structure can harm market stability and price discovery by adversely affecting the proportion of skilled traders. Centralised markets protect unskilled traders from the consequences of bad decisions by allowing them to free-ride on the prices discovered by skilled traders. The incentives to acquire skills are weak in more centralised markets, and, in equilibrium, most traders are unskilled. This is in contrast to fragmented markets where mistakes are exploited by skilled traders and therefore most traders are skilled in equilibrium. As a result, fragmented markets are more resilient and provide better price discovery. Inter-market price variation, defined as the variation in prices between trading venues is, however, increasing in market fragmentation.

Regulators are concerned with the potential lack of competition amongst exchanges; economies of scale and network externalities make these institutions natural monopolies (Mendelson, 1987). Regulations such as MiFID in Europe and Regulation ATS and RegNMS in the US aimed to increase competition for order flow (Fink et al., 2006). As a consequence there has been a rise in the number of alternative trading venues such as crossing networks and dark pools which attract traders away from the main exchanges (Stoll, 2008). Despite the increase in the number of places to trade, the US market, for instance, has been described by O'Hara and Ye (2011) as a 'single virtual market with multiple points of entry'.

Market centralisation during the last two decades has been accompanied by a dramatic increase in the stock market participation of non-professional investors (Bogan, 2008) who adopt investment strategies without fully understanding the risks (Bikhchandani et al., 1998). Our model shows that the increase in the proportion of unskilled traders following market centralisation is an equilibrium phenomenon.

Section 2 sets out a model of a market with multiple trading venues and endogenous skills. Section 3 presents results on the relationship between market fragmentation and the prevalence of skills, and its the consequences for price volatility and market resilience. The section also illustrates the effect of market centralisation under an inflow of unskilled bullish investors. Section 4 concludes.

2 Model

We consider a finite population of I traders who exchange option contracts in trading venues of size N. Venue size is fixed within a market and ranges from $N = I$ where trade is centralised at one trading venue to $N = 2$ where all trade is bilateral. Traders participate in a sequence of trading rounds. In each round, traders are randomly assigned to trading venues. An option contract is then randomly drawn from a continuum of possible contracts at each venue, traded, and (imperfectly) hedged until maturity. After expiry, a new trading round begins.

Market. The buyers and sellers of the contract at a venue are determined as follows. All traders simultaneously quote prices at which they are indifferent between buying and selling one option contract. An equilibrium price at each trading venue is then defined as the median of these quotes. At this price supply is equal to demand. Traders with quotes above (below) the market price buy (sell) one unit of the contract. Ties are resolved by randomly assigning traders to be buyers and sellers. To avoid non-participation, we take the venue size N to be an even number.

All contracts are European call options with a maturity of three months. The price dynamic of the underlying asset follows a geometric Brownian motion

$$dS(t) = \mu S(t)dt + \sigma S(t)dW(t)$$

with drift μ and volatility σ. Traders also have access to a money market with interest rate r. Time is measured in years and the parameter values for drift, volatility and interest rate are given per annum. The initial spot price

$S(0)$ is fixed at 100 without loss of generality due to the scalability of the price process.

An option contract is defined by a strike price K and the values of σ and r. The drift μ is held constant across all contracts as it has a negligible impact on the optimal hedge.

Gains and losses. At each issue date, a random option contract is drawn according to Table 1; its price is established at each venue and traders exchange premiums. Traders then hedge their exposure to the option contract until maturity by trading in the underlying asset and the money market. At the beginning of each trading day, their portfolio is adjusted to match the Black-Scholes delta-hedging strategy. At maturity, sellers pay the option payoff (if any) to buyers.

The profit of a call option writer who delta-hedges the short position in the 3-month option at times $t_n = n\,\Delta t$ with $n = 0, 1, ..., 65$ and $\Delta t = 1/264$, from the issue time $t_0 = 0$ to the time of expiry $T = t_{66}$ evolves as:[1]

$$v(t_{n+1}) = e^{r\Delta t}[v(t_n) - \phi(t_n)S(t_n)] + \phi(t_n)[S(t_{n+1}) - S(t_n)]$$

where

$$\phi(t_n) = \Phi\left(\frac{\log(S(t_n)/K) + (r + \sigma^2/2)(T - t_n)}{\sigma\sqrt{T - t_n}}\right)$$

and Φ is the standard normal cumulative distribution function, $v(0) = 0$.

[1]For simplicity we assume that the 66 trading days from issue to maturity, a quarter of the annual 264 trading days, are equally distributed across time.

With option price C, the seller's payoff at maturity is

$$\Pi = Ce^{rT} + v(T) - [S(T) - K]^{+} \tag{1}$$

and that of the buyer is $-\Pi$ because premium payments, hedge positions and payments at maturity net to zero. Since the hedging strategy is not continuous, it provides only an imperfect hedge. There is, therefore, a stochastic element to the returns from all options.

Learning. Traders apply individual pricing functions to determine their quote. A pricing function associates a real number to any combination of values of the three option parameters: strike price, volatility and interest rate. Contrary to standard asset pricing models, traders in our model do not solve an explicitly formulated optimisation problem. Instead pricing skills result from experience.

An evolutionary learning process is applied to model traders' choice of pricing functions. The pricing functions present in the trader population evolve over time through (a) the imitation of successful pricing functions and (b) innovation through random modifications of these functions. Success is measured relative to the market rather than some artificial benchmark. A trader's pricing function is more successful than that of another trader if, on average, it produces higher gains in wealth. The evolutionary learning process therefore takes place on the level of the population rather than that of the individual.

We represent the learning process by a genetic programming algorithm with tournament selection as in Lensberg and Schenk-Hoppé (2007). Pricing functions are implemented as computer programmes. A programme is a list of up to 256 instructions. Each instruction consists of an operator and one or two operands. The set of operators is $\{+\ ,\ -,\ /,\ \times,\ \max,\ \min,$ change sign, exp, log, $\Phi\}$, where Φ is defined above. Operands consist of the three option parameters (strike, volatility and interest rate); 2^{13} numerical constants; and three temporary variables. Traders price options by executing their programmes. Their quotes are given by the value of the first temporary variable on completion of the programme.

To model market exit and entry, imitation and innovation, we use tournaments that are run after each option is traded and the payoffs calculated. Initially each trader is assigned a random pricing function. A trader continues using a pricing function until he is replaced by a new trader according to the following algorithm:

1. *Tournament:* Randomly (and uniformly) select four traders in the population and rank them by accumulated wealth.

2. *Reproduction:* Replace the programmes of the two with the lowest rank by copies of those of the two with the highest rank.

3. *Crossover:* With probability χ_1, swap two randomly selected sublists of instructions of equal length between the two programmes.

4. *Mutation:* For each programme, with probability χ_2, a single operation or operand in a programme is randomly selected, and replaced by a new random operation or operand.

All new traders enter the market with zero wealth. Accumulated wealth

Table 1: Parameter values.

Number of traders I	varies 2,000; 4,000; 8,000
Trading venue size N	varies 2; 4; ...; 128; 250; 500; 1,000; 2,000
Stock price volatility σ	uniformly drawn from $[10\%, 30\%]$
Interest rate r	uniformly drawn from $[1\%, 6\%]$
Strike price K (spot price is 100)	uniformly drawn from $[80, 120]$
Drift μ	6%
Discount rate τ	1% (per annum)
Tournaments per period	$0.5\% \cdot I$
Penalty if quote < 0 or > 40	5
Crossover probability χ_1	0.50
Mutation probability χ_2	0.95

is discounted. Each 3-month period, the positive (negative) wealth V of a trader is reduced (increased) to $(1 - \tau/4)V$ with τ the annual discount rate. Discounting preserves wealth ratios and rankings in tournaments, but speeds up the process by which poor traders with good pricing theories can overtake wealthy traders with inferior ones.

Data set. Parameter values used in the numerical simulation are presented in Table 1. For each combination of venue size and population size, we carry out 50 independent simulation runs. Runs differ with respect to the composition of the initial population, the option contracts to be priced, the assignment of traders to venues, and the evolution of pricing functions. The pricing functions of the converged models are recorded and used to generate data for the statistical analysis.

We use four different criteria to explore how the characteristics of the option market change with the degree of centralisation. These measures are based on a fixed, representative set $\mathcal{C}$ of 27 option contracts. This set is given by all combinations of the following parameter values:

$$\sigma = 0.15, 0.2, 0.25;\ r = 0.02, 0.035, 0.05;\ \text{and } K = 95, 100, 105. \tag{2}$$

Traders' pricing decisions on this set of options are evaluated only to collect data; there is no corresponding change in their wealth.

The performance criteria are:

Skill as a measure of the proportion of traders who can correctly price all contracts in the set $\mathcal{C}$. A trader is said to be skilled if her quotes do not deviate by more than 10% from the median of the quotes of all traders in the population. Using the median price in defining skill ensures that all traders are evaluated against the same benchmark.

Price volatility measures the time-series variability of consolidated option prices. For each contract in $\mathcal{C}$, it is the volatility of the time series consisting of the median market price across all trading venues at each point in time. Price volatility is the average of these volatilities across all contracts in $\mathcal{C}$.

Price dispersion is a measure of the variability in option prices across trading venues. For each contract in $\mathcal{C}$ and each point in time, the standard deviation of the cross-section of market prices is calculated. Price dispersion is the average of these standard deviations over time.

Price sensitivity is measured by exposing the market to shocks in terms of entries into the market by traders with extreme option valuations. Let $P(0)$ be the median quote in the population without additional traders, and let $P(M)$ resp. $P(-M)$ denote the median quote when $M > 0$ additional individuals who post the highest resp. lowest feasible quote are added to the market. For each value of M, we calculate the corresponding price sensitivity

$$\frac{P(M) - P(-M)}{P(0)} \bigg/ \frac{M}{I} \tag{3}$$

and average over 50 independent observations and all 27 out-of-sample options in $\mathcal{C}$. The shock size M can take values 1%, 2%, 5%, 10%, 20%, 40%, and 80% of the population size I.

Table 2 provides summary statistics on the four performance measures. With 33 different combinations of population and venue sizes[2] and 50 independent runs, one has a maximum of 1,650 observations of skill, price volatility and price dispersion. For price sensitivity, which is measured for 7 different shock sizes, we therefore have 11,550 observations. Except for skill, these measures display a considerable amount of positive skewness in the distributions of the dependent variables. In the regressions we therefore use the log-transformed versions of those measures as the dependent variable. We disregard the venue size $N = 2{,}000$, when $I = 2{,}000$, as price dispersion is zero in this case.

Table 2: Summary statistics for dependent variables.

Statistic	Sample Size	Mean	Std. Dev.	Min.	Median	Max.
Skill	1,650	0.344	0.256	0.000	0.278	0.899
Price volatility	1,650	0.028	0.025	0.0004	0.022	0.199
Price dispersion	1,500	0.228	0.452	0.001	0.058	4.206
Price sensitivity	11,550	0.551	1.039	0.003	0.200	11.815

[2] The maximum venue size is 2,000 for all population sizes to ensure that these variables are orthogonal.

3 Results

The discussion of the results follows the list of performance measures: skill, price volatility, price dispersion and price sensitivity. These measures capture (a) the benefit of knowledge relative to the costless option of free-riding on other traders' ability to make good decisions, (b) time-series as well as (c) cross-venue variation of option prices which would both be zero in a frictionless market with only skilled traders, and (d) how well the market responds to exogenous shocks to demand or supply.

The statistical analysis of the performance measures uses independent variables drawn from the model: market centralisation measured as $\log(N)$ (the natural logarithm), where N is the size of a venue, and population size measured as $I/1000$. In addition, we define a dummy variable 'Fragmented' to distinguish between markets that are highly fragmented and those that are not. The dummy variable is set to 1 for markets with venues of 250 traders or less. At about this venue size the dependent variables exhibit a structural break when plotted against venue size.

3.1 Skills

We first investigate how skill varies with the environment in which the traders interact. The key variable controlling this environment is market centralisation, which we expect to have a negative impact on the proportion of skilled traders. Three model specifications are used: Model (1) measures the overall impact of market centralisation on skill, model (2) considers whether the effect of centralisation differs between markets that are more or less fragmented at the outset, and model (3) looks at the effect of population size. Table 3 provides the estimation results.

Table 3: Proportion of skilled traders. Data from 50 independent simulation runs for each combination of venue size and population size listed in Table 1. The dummy variable 'Fragmentation' is set to 1 for markets with venues of 250 traders or less. Robust standard errors in parentheses.

	Dependent variable:		
	Skilled traders (percent)		
	(1)	(2)	(3)
Constant	71.320***	13.303*	7.544
	(0.939)	(7.319)	(7.281)
Centralisation	−8.900***	0.235	0.235
	(0.187)	(1.067)	(1.046)
Centralisation × Fragmented		−12.453***	−12.453***
		(1.104)	(1.082)
Population size (1000's)			1.234***
			(0.154)
Fragmented		66.452***	66.452***
		(7.393)	(7.266)
Adjusted R^2	0.574	0.630	0.644
Observations	1,650		
Note:			*p<0.1; **p<0.05; ***p<0.01

Market centralisation negatively affects the proportion of skilled traders: The coefficient of the centralisation variable in model (1) is negative and highly significant, and the model produces a good fit with $R^2 = 57.4\%$. The smaller proportion of skilled traders in more centralised markets is directly related to the possibility to free-ride. This possibility arises if (a) the market price belongs to the convex hull of prices quoted by one or more skilled traders, and (b) one can quote an extreme price without impacting the market price. In this case the market price is fair and all traders exchange contracts at this fair price.

In centralised markets there are many traders at each venue; hence the price impact of an individual quote is small. In bilateral trade, both traders have a strong price impact as each quote contributes a half of the market price. This scenario generates the highest number of skilled traders. Model (1) confirms the hypothesis that the possibility to free-ride on others' skills provides an incentive for traders to not acquire skills. The more centralised the market, the stronger is this incentive. In general, the higher price impact of individual quotes in more fragmented markets puts more pressure on traders to develop skills. For instance, in a population of size $I = 8{,}000$, when trade is bilateral, 74% of the population is skilled, while this proportion is only 19% under fully centralised trade.

Model (2) controls for the size of price impact of individual quotes by adding a dummy variables that is 1 for venue sizes of 250 or less. The estimation results show that the effect of increased venue size on skill is limited to markets that are relatively fragmented. In highly centralised markets, further centralisation does not decrease skill.

The effect of the population size is explored in model (3). In our data set the smallest population consists of 2,000 traders. Model (3) shows that greater population sizes have little effect on trading skills. Although this variable (measured in thousands) has a statistically significant positive effect on skills, it adds just over 1 percentage point to the explanatory power of the regression.

As the skills of traders are most valuable in fragmented markets, skilled traders prefer more fragmentation over less. The opposite is true for unskilled traders. In supporting large numbers of unskilled traders along with a few skilled ones, the centralised exchanges in our model resemble those examined by Oliven and Rietz (2004). Unskilled traders only have a small effect on the price and receive very little feedback on their strategy; instead they free-ride on the skills of others. Fragmented markets reduce the ability of individuals to do this, forcing traders to develop pricing skills to avoid losing money. Barber and Odean (2001) observe that with easier market access through internet trading, there has been a growth in free on-line advice. Traders can base their decisions on this information and, without requiring any skill, free-ride.

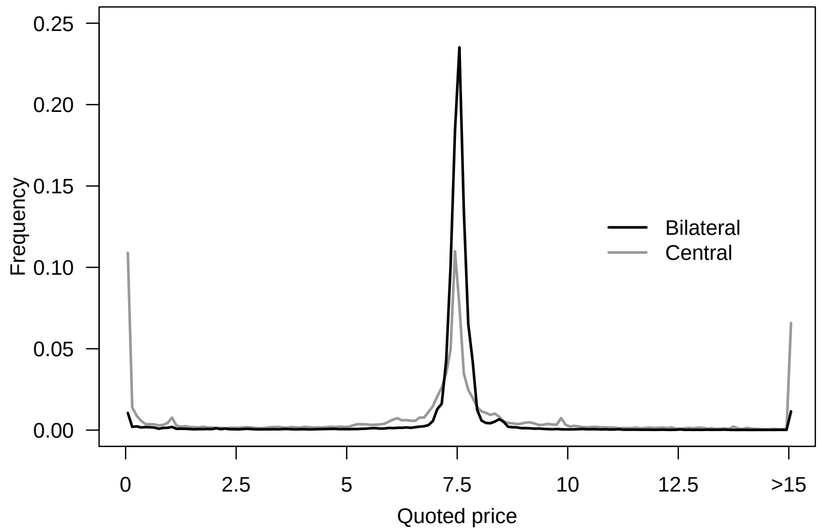

Figure 1: Histogram of traders' price quotes under centralised trade $N = I$ (grey line) and bilateral trade $N = 2$ (black line). Trader population size $I = 4{,}000$. Histogram calculated over 50 independent model simulations for each value of N.

The impact of market fragmentation on the distribution of quotes is illustrated in Figure 1. It shows all quotes for one particular option contract in the two extreme scenarios of bilateral and fully centralised trade. In both markets there is a large proportion of traders whose quotes are close to the fair value of the option. In the fragmented market this proportion is considerably higher due to the higher number of skilled traders. The centralised market contains two large groups of unskilled traders who quote either very high or very low prices for the option. These traders possess no proper theory for the fair value of the option but choose to free-ride. As the number of free-riders is an equilibrium outcome, unskilled and skilled traders are equally well off at the option prices determined by the skilled traders' quotes.

3.2 Volatility

Market fragmentation comes with the loss of a single, global price as each venue can have a different, local price. This does not imply that the informational efficiency of fragmented markets is necessarily lower. An outsider can use all of the information revealed in the process of trading to extract a consolidated price, information that is, ex ante, not available. Suppose the same option is traded at each venue, then the median of all traders' quotes can be calculated ex post. In a fully centralised market with venue size equal to population size, the consolidated price is identical to the market price. In fragmented markets it will usually be different. We therefore examine the impact of market fragmentation on the time-series properties of consolidated prices as well as the cross-sectional variation in realised prices. The model setup is the same as for skills. Table 4 presents the results for time-series volatility.

Model (1) reveals that the time-series volatility of the consolidated price

Table 4: Price volatility. The regression is calculated using OLS and robust standard errors. Standard deviations calculated from time series of length 10,000 for each of 50 independent runs for each combination of venue size and population size listed in Table 1. The dummy variable 'Fragmentation' is set to 1 for markets with venues of 250 traders or less. Robust standard errors in parentheses.

	Dependent variable:		
	Log(Price volatility)		
	(1)	(2)	(3)
Constant	-5.873^{***}	-3.188^{***}	-2.910^{***}
	(0.047)	(0.390)	(0.385)
Centralisation	0.426^{***}	0.002	0.002
	(0.009)	(0.057)	(0.055)
Centralisation × Fragmented		0.579^{***}	0.579^{***}
		(0.058)	(0.057)
Population size (1000's)			-0.060^{***}
			(0.007)
Fragmented		-3.081^{***}	-3.081^{***}
		(0.393)	(0.385)
Adjusted R^2	0.591	0.646	0.661
Observations	1,650		
Note:			*p<0.1; **p<0.05; ***p<0.01

process increases with centralisation. A fragmented market therefore produces more reliable information on the fair value of the option. As illustrated in Figure 1, a fragmented market displays a higher density of quotes around the median price. The consolidated price is therefore less prone to change in response to noise from unskilled traders' decisions.

Higher volatility of consolidated prices in more centralised markets is directly related to the declining proportion of skilled traders due to centralisation. As skills react most strongly to centralisation when a market is already fragmented, we would expect the same behaviour for price volatility. This hypothesis is supported by model (2). All of the effect of centralisation is captured by the cross-term which controls for the ex ante size of venues. The same mechanism governing the effect of centralisation on skill in fragmented markets appears to drive its impact on time-series volatility. Population size has only a small effect on volatility which is lower for larger populations. This observation mirrors the small but positive effect of population size on skills which is reported in Table 3, model (3).

From an economic perspective, centralisation of fragmented markets is the main contributor to increased time-series volatility. The R^2 of model (2) at 64.6% is higher than in model (1) but only slightly lower than in the full model (3). Our observation on the role of fragmentation on price volatility is consistent with Smith et al. (1988)'s finding that markets with a large proportion of unskilled or inexperienced traders have larger price fluctuations.

Fragmented markets, while producing a consolidated price signal with lower time-series volatility than centralised markets, generate many different trade prices; possibly as many as there are venues. Since time-series variation does not capture this effect, we also analyse the cross-sectional variation of prices. Table 5 shows the results.

Cross-sectional price variation decreases with market centralisation, see model (1). The explanatory power of the centralisation variable is high with an $R^2 = 67.0\%$. Model (2) shows that the effect of centralisation on price dispersion is not significantly different in markets that ex ante are more fragmented or more centralised.

The uniform impact of centralisation on price dispersion is the result

Table 5: Price dispersion. The regression is calculated using OLS and robust standard errors. Standard deviations averaged over time series of length 10,000 for each of 50 independent runs for each combination of venue size and population size listed in Table 1. The maximum venue size is set as 1,000 because price dispersion is zero if there is only one market. The dummy variable 'Fragmentation' is set to 1 for markets with venues of 250 traders or less. Robust standard errors in parentheses.

	Dependent variable:		
	Log(Price dispersion)		
	(1)	(2)	(3)
Constant	-0.425^{***}	0.806	1.017
	(0.051)	(0.818)	(0.833)
Centralisation	-0.577^{***}	-0.726^{***}	-0.726^{***}
	(0.011)	(0.123)	(0.125)
Centralisation × Fragmented		0.065	0.065
		(0.124)	(0.126)
Population size (1000's)			-0.045^{***}
			(0.008)
Fragmented		-1.031	-1.031
		(0.820)	(0.834)
Adjusted R^2	0.670	0.686	0.692
Observations	1,500		
Note:			*p<0.1; **p<0.05; ***p<0.01

of two different forces working in opposite directions because centralisation impacts the proportion of skilled traders as well as the size of venues. In more fragmented markets there are many venues but also many skilled traders. This leads to a situation where prices at many venues are close to the fair value. To see that this claim holds true, consider the differences in the distribution of quotes in Figure 1. When the majority of traders at a venue are skilled, or if there are enough skilled traders to make up the difference between the number of unskilled buyers and unskilled sellers, the quote will be close to the fair value. Hence many prices in a fragmented market will be fair. In more centralised markets there are few venues but many unskilled traders. The law of large numbers implies that unskilled buyers and sellers at each venue resemble closely their proportion in the whole population, where their proportions are identical on average. In this case a small number of skilled traders suffices to produce prices close to the fair value. The result in model (2) shows that the two forces, the impact on the size of the venue and the number of skilled traders, are about equal. Population size, included in model (3), only has a minor impact on price dispersion.

We conclude that, from an economic point of view, further centralisation has the same positive effect on the cross-sectional price dispersion in more fragmented as well as more centralised markets. Our results on time-series and cross-sectional volatility mirror those in Madhavan (1995). Skilled traders in our model effectively act as market makers; they set the market price and are willing to take either side of the contract at this price. With endogenous skills, fragmented markets do produce highly volatile prices at each venue, however, the information revealed through trade is better than in a centralised market.

3.3 Resilience

We measure the impact of centralisation on market resilience using price sensitivity, see (3). This measure captures the response of the consolidated price signal, i.e. the median of all traders' quotes, to exogenous shocks which are modelled as the market entry of traders with extreme valuations of the option contract. Lower price sensitivity is associated with higher market resilience. Table 6 collects the results.

Table 6: Price sensitivity. Statistics for the regression are calculated for the 27 test options on 50 independent runs for each combination of venue size and population size listed in Table 1. The dummy variable 'Fragmentation' is set to 1 for markets with venues of 250 traders or less. Robust standard errors in parentheses.

	Dependent variable:		
	Log(Price sensitivity)		
	(1)	(2)	(3)
Constant	-3.377^{***}	-1.259^{***}	-0.921^{***}
	(0.025)	(0.242)	(0.238)
Centralisation	0.414^{***}	0.081^{**}	0.081^{**}
	(0.005)	(0.035)	(0.034)
Centralisation $\times$ Fragmented		0.451^{***}	0.451^{***}
		(0.036)	(0.035)
Population size (1000's)			-0.072^{***}
			(0.004)
Fragmented		-2.420^{***}	-2.420^{***}
		(0.244)	(0.239)
Adjusted R^2	0.366	0.387	0.402
Observations	11,550		
Note:			*p<0.1; **p<0.05; ***p<0.01

Model (1) shows that price sensitivity increases with market centralisation. This is a direct effect of the loss of skill. Fragmented markets absorb shocks better than centralised markets because the higher proportion of skilled traders leads to a larger number of quotes close to the consolidated price. Model (2) provides separate estimates for fragmented markets. In this model, the coefficient on the overall centralisation variable is still significantly positive at the 5% level. This indicates that the effect of centralisation on price sensitivity is not limited to markets that are relatively fragmented, in contrast to the results obtained for skill and volatility. Population size has a small positive effect on market resilience, model (3).

The difference in resilience between fragmented and centralised markets is illustrated in an example. We consider a scenario in which a market attracts unskilled bullish traders over a prolonged period in time. The quotes of these traders are always considerably above the maximum value of all options considered and, therefore, will increase the median quote in the population. The effect will be stronger, the sparser the distribution of quotes close to the median quote. We analyse two cases of different degrees of market centralisation. In the first case, trade is bilateral, and in the second case, trade is centralised at one venue. The initial trader population at time zero in both cases is taken from the equilibrium of the bilateral market with 4,000 traders. During a period of length 5,000, each time-step sees the entrance of one unskilled bullish trader with 50% probability. Afterwards the market evolves without being subject to further exogenous shocks.

Figure 2 shows time series of the consolidated price of one representative option, and the proportions of skilled traders, unskilled buyers and unskilled sellers. Unskilled buyers (sellers) are traders whose quotes are at least 10% above (below) the market price for all options. Panel (a) shows that in the bilateral market an exogenous inflow of bullish traders increases the average price to levels well above the fair value. As soon as the inflow of new buyers stops, both the price and the number of unskilled buyers fall back to their original levels and the market returns to its equilibrium.

Panel (b) in Figure 2 depicts the scenario in which the inflow of bullish traders coincides with a change in market structure from bilateral to centralised trade. The inflow leads to a period during which the option is over-

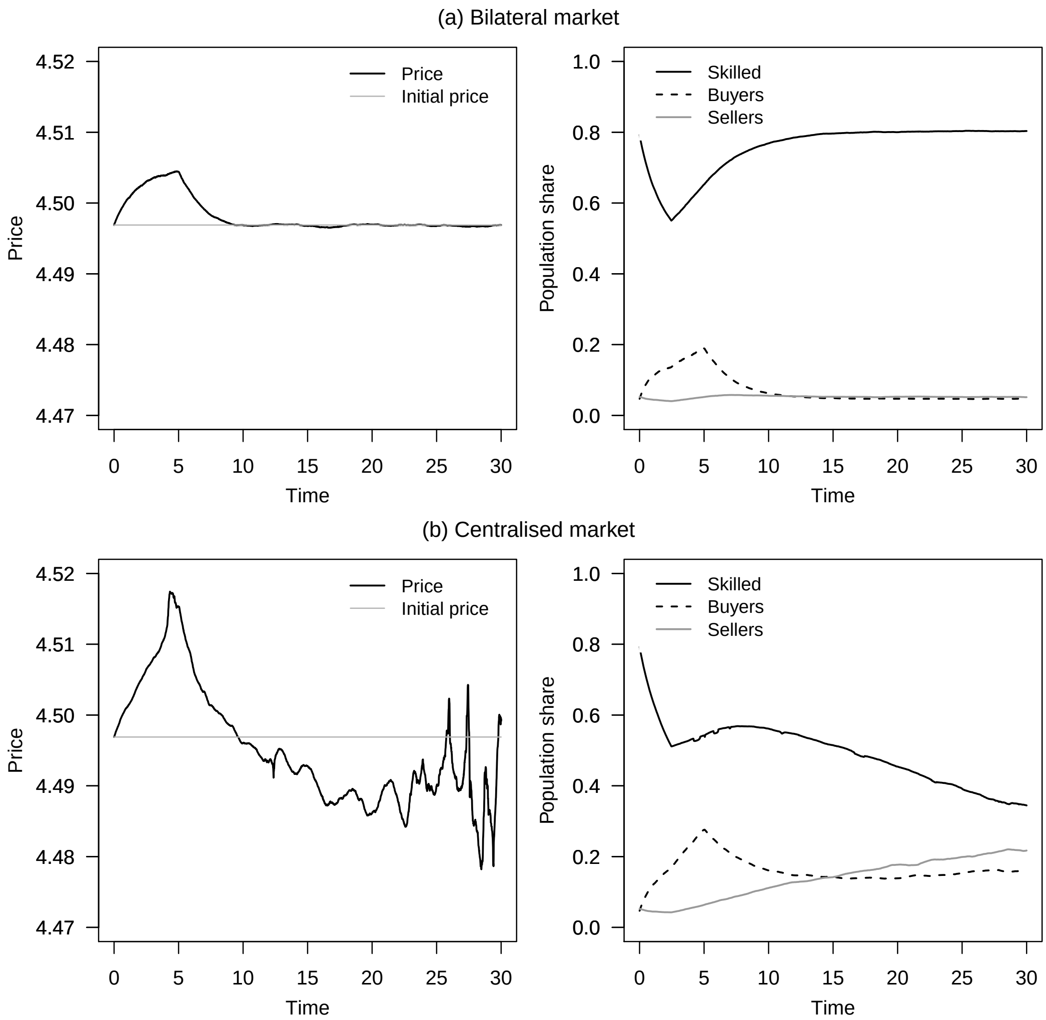

Figure 2: Market price and frequency of trader types in a bilateral market (Panel (a)) and in a centralised market (Panel (b)). Initial population of 4,000 traders taken from a market with bilateral trade. Arrival of bullish traders with constant quote equal to 40 during the first 5,000 periods (in each period, with probability 0.5, one such trader is added). Time in units of 1,000. Left-hand panels: time series of median quote of one option market (black) and the option's fair value (grey). Right-hand panels: percentage of skilled traders, unskilled buyers (including those exogenously added) and unskilled sellers.

valued. The price rises by more than in the bilateral case because the decline in the proportion of skilled traders is more pronounced. Unskilled sellers outperform unskilled buyers and do at least as well as skilled traders (who are both on the same side of the market as unskilled sellers). Therefore the proportion of unskilled sellers grows at the expense of skilled traders. As soon as the demand from the new buyers is removed, the price sharply declines and undershoots the fair value. Price volatility increases as skilled traders are replaced by unskilled ones. This is caused by the diminishing benefit of possessing skills in more centralised markets. To put the negative effect into perspective, we note that initially 76% of the traders are skilled but, by period 30,000 (not shown in figure), their proportion is reduced to 28% and asymptotically becomes 5.6%. In contrast, the proportion of unskilled buyers and sellers increases from 12.6% to 62.4%.

4 Conclusion

The paper demonstrates that the ability of traders to make good decisions, rather than taken for granted, can be considered as an equilibrium phenomenon. To this end, we propose a model where skills are endogenous. We study the effect of market centralisation on the prevalence of traders with skills. We find that centralised markets generate the lowest proportion of skilled traders while bilateral trade generates the highest. This has implications for market resilience and price discovery. Both are highest when all trade is bilateral and lowest in centralised markets. These benefits, however, come at the cost of higher price dispersion across trading venues. Our results suggest that the cost efficiency and transparency of a centralised market must be weighed against better price discovery and market resilience under decentralised trade.

By viewing skills as endogenous to markets, our findings highlight a hidden cost of moving the trade of complex assets towards centralised exchanges. While it may be socially desirable to have an asset traded at one price, centralising trade to protect unskilled investors from the consequences of their foolish behaviour can be counterproductive for market stability and price efficiency.

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